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S. A. Klein, A. Hall

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Stephen A. Klein[1] and Alex Hall[2]

[1]Program for Climate Model Diagnosis and Intercomparison, Lawrence Livermore National Laboratory, Livermore, California, USA

[2]Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, Los Angeles, California, USA

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Corresponding author: Stephen A. Klein, Program for Climate Model Diagnosis and Intercomparison, Lawrence Livermore National Laboratory, 7000 East Avenue, L-103, Livermore, CA 94551. (klein21@llnl.gov)

Abstract

Emergent constraints are physically explainable empirical relationships between characteristics of the current climate and long-term climate prediction that emerge in collections of climate model simulations. With the prospect of constraining long-term climate prediction, scientists have recently uncovered several emergent constraints related to long-term cloud feedbacks and climate sensitivity. We review a number of these proposed emergent constraints, many of which involve the behavior of low-level clouds, and discuss criteria to assess their credibility. With further research, the cases we review may eventually become true emergent constraints, as they each have candidate physical explanations that are credible.

Because credible emergent constraints identify a source of model error that projects onto climate predictions, they deserve extra attention from those developing climate models and climate observations. While a systematic bias cannot be ruled out, it is noteworthy that the more credible potential emergent constraints suggest larger cloud feedbacks and climate sensitivity.

1. What is an emergent constraint?

When combined with the power of human mind to assess the physical plausibility of their predictions, comprehensive climate models are the most powerful tools available to predict future climate and its response to radiative forcings such as the anthropogenic increase in greenhouse gases. Unfortunately model predictions for key metrics of climate change do not converge to a single value. The most prominent example is the climate sensitivity, defined as the equilibrium warming resulting from a doubling of carbon dioxide. It varies by at least a factor of 2 in the most recent collection of models used for climate change assessment (IPCC 2013), much as it has in all past model collections.

In this situation, scientists attempt to assess the relative credibility of model predictions using their insight. Often they appeal to the principle that models unable to predict past climate variations skillfully should not be trusted for future climate predictions. However, with past climate variations such as the global warming of the past century, or glacial-interglacial transitions of the Pleistocene, there are uncertainties in the observed forcing as well as the response. In addition, past climate forcings differ in important ways from that resulting from changes in carbon dioxide alone. Thus, past climate variations are an incomplete lens through which to judge the credibility of a climate model's future predictions. More practically, they do not offer the ability to appreciably narrow the range of climate sensitivity estimates beyond that of the models (Kiehl 2007, Knutti 2008, Masson-Delmotte et al. 2013).

The climate of the past few decades is well observed enough to characterize basic statistics of key climate variables such as mean state, variability, and trends. A more basic if less direct principle than verifying the models against past climate response to external forcing is that models failing to reproduce these statistics should not be trusted for future climate prediction. Past attempts following this line of reasoning suggest climate sensitivities in the upper half of the currently accepted range are more realistic (Murphy et al. 2004, Knutti et al. 2006, Huber et al. 2011). But which aspect of the current climate is important for its climate prediction? It seems intuitive that realistic simulation of the current climate for variable *x* (temperature, clouds, or something else) would lead to a more believable prediction of the change in *x*. But there is no evidence this has to be true, and the processes shaping future response in *x* may be quite distinct from those shaping *x* in the current climate. For example, the water vapor, lapse rate, surface albedo, and cloud feedbacks determining climate sensitivity are not the most important processes determining the current climate's geographical and seasonal temperature distribution, a common observational target for climate model development. This raises the question as to whether there is any better way to decide which quantities of the current climate are relevant for climate change.

So-called 'emergent constraints' answer this question by examining the inter-model spread that *emerges* in collections of climate models such as those assembled for the 3rd and 5th phases of the Coupled Model Intercomparison Project (CMIP) (Meehl et al. 2005, Taylor et al. 2012). Specifically, an emergent constraint is a strong empirical relationship between inter-model variations in a quantity describing some aspect of recent observed climate and the inter-model variations in a future climate prediction of some quantity. Once combined with an observational estimate of the quantity from the current climate, the future prediction may be *constrained* provided (a) the observational uncertainty is less than the inter-model spread, (b) the observed value falls within the range of model results, and (c) the future climate quantity is a single-valued function of the current climate quantity. However, because the constraint may be fortuitous, a relationship should not be termed an emergent constraint unless it is accompanied by a plausible physical explanation and satisfies other additional criteria (to be proposed below).

The earliest and still most robust emergent constraint is that for the snow-albedo feedback (Hall and Qu 2006, Qu and Hall 2014). A strong linear relationship exists between (a) inter-model spread in the seasonal cycle change in surface albedo over northern hemisphere land per degree surface warming and (b) the change in surface albedo per degree surface warming in simulations of climate warming resulting from increases in greenhouse gases (Figure 1). Considering an observational estimate of the seasonal cycle change, a surface albedo feedback in the middle range of model results would seem to be more likely. The underlying physical assumption is that the modeled physical processes of how surface albedo changes with the large warming during the seasonal cycle are manifest for the smaller warming associated with climate change. This physics is corroborated by the fact that in the contexts of both seasonal cycle and climate changes, the feedback is controlled mainly by the simulated surface albedo in snow-covered areas. More recently, Cox et al. (2013) have identified an emergent constraint for the global warming sensitivity of carbon stored in tropical lands from the sensitivity of the annual CO_2 growth rate to inter-annual tropical temperature anomalies. However, the robustness of this constraint has been questioned using a different model ensemble (Wang et al. 2014).

Given its overwhelming importance, climate sensitivity has proven an attractive target for research on emergent constraints. Since cloud feedbacks are a leading contributor to inter-model spread in climate sensitivity (IPCC 2013), emergent constraints for climate sensitivity necessarily include cloud feedbacks either directly or indirectly. However, cloud processes may be significantly more complex than processes for which robust emergent constraints have already been found, such as surface albedo feedback. For this reason, we begin by suggesting strict reliability criteria that could be used to gauge the significance and credibility of any proposed emergent constraint on cloud feedback. Then, we review recently proposed emergent constraints for cloud feedbacks and climate sensitivity. The final section will discuss the implications of emergent constraints for model development, observational science, and climate prediction.

2. Reliability criteria for emergent constraints

The correlation underlying all potential emergent constraints could simply be coincidental. On what basis could one declare the correlation a true emergent constraint? We offer the following reliability criteria.

Strong physical basis. Foremost is the need for a physical explanation of the empirical relationship between current and future climate parameters. This should account for how differences in model structure contribute similarly to spread in the current and future parameters. The physical understanding should also explain why the relationship exists (or not) across the time-scales spanning the current climate and future climate change (e.g. daily, seasonal, inter-annual, or inter-decadal).

The challenges here are two-fold. The first is identifying a physical mechanism. Ideally, this should point to specific physical parameters, parameterizations, or their interactions. Furthermore, the physical understanding should permit quantitative explanation of inter-model variations in current and future climate parameters. Ideally, it should also be possible to assess which model parameterizations are more reliable through comparison with observations. In the case of cloud feedback, benchmark models such as Large-Eddy Simulations (*LES*), simulations by very high-resolution limited-area models that resolve the fine-scale circulations that form clouds, may substitute for observations given that observations of complex cloud processes are insufficient.

The second challenge is demonstrating convincingly that the physical mechanism is at work in the model ensemble. This requires either in-depth diagnostics or model experimentation, or both. For diagnostics, the existing model archives are often insufficient or incomplete. For cloud feedbacks, examples of the necessary diagnostics include parameterization-specific quantities such as the tendencies for individual processes such as large-scale cloud microphysics and macrophysics, shallow convection, deep convection, turbulence and large-scale dynamics (Ogura et al. 2008).

Direct model experimentation is a more powerful way to demonstrate the physical basis of an emergent constraint. For example, if the cause of inter-model variations can be traced to parameterization of a single process, current climate and climate change simulations could be performed with alterations to that parameterization. Even if a single parameterization cannot be isolated, some support for a physical mechanism could come through testing the physical processes likely to be involved, such as cloud physics, convection, turbulence, or radiation. Testing can be performed by perturbing fixed parameters (Murphy et al. 2004, Klocke et al. 2011) or replacing whole parameterizations in a single model (Watanabe et al. 2012, Zhao 2014). Coordinated multi-model experiments such as those organized by the Cloud Feedback Model Intercomparison Project (Bony et al. 2011) disable or alter various model components, such as the parameterizations of convection or cloud radiative effects (Fermepin and Bony 2014, Webb et al., *The impact of parametrized convection on cloud feedback*, in preparation). Because they sample greater model structural diversity, such experiments are potentially more valuable than those involving perturbations to a single model. Ultimately, all model experimentation is convincing only if it is simultaneously connected to a physical mechanism that explains how the model changes contribute similarly to inter-model variations in current and future climate parameters.

A plausible physical explanation is by far the most important criterion for an emergent constraint. However, when a physical explanation is only partially developed, the following two subsidiary criteria can also be considered, in the sense that if they are satisfied, they make it more likely that a compelling physical explanation exists.

Robustness to choice of model ensemble. Except in the unlikely case that the modeling groups had simultaneously learned of an emergent constraint and substantially removed inter-model spread in the associated current climate predictor, one would expect an emergent constraint to be manifest in the various collections of climate models (e.g. CMIP3 and CMIP5). Similarly, in absence of a physical explanation, one must view with suspicion an emergent constraint that appears in a perturbed-parameter ensemble of one climate model but not in the structurally more diverse CMIP ensembles (Klocke et al. 2011).

No obvious multiple influences. It is difficult to establish the robustness of an emergent constraint for quantities subject to multiple influences. An illustrative example is the case of equilibrium climate sensitivity, which depends on a number of independent feedbacks. Each of these contributes to inter-model variance (Webb et al. 2012). It would not be appropriate to seek an emergent constraint for climate sensitivity. Even if one could find correlated current and future climate parameters in this case, one might declare a model that agreed with observations due to compensating errors in the underlying feedbacks to be more realistic than a model that did not agree with observations due to a bias in one feedback even though all of the other feedbacks were correct. Clearly, forcing the models to be realistic in the current climate parameter would not necessarily lead to a spread reduction in climate sensitivity for the right reasons, if at all. So the proposed emergent constraint would have little value. It is only valuable to seek emergent constraints that target individual processes, such as the snow-albedo feedback or aspects of cloud feedback.

In the case of cloud feedback, the inherent complexity of cloud physics makes it is difficult to find emergent constraints that target individual processes. One reason we find the well-developed examples in this paper compelling is that they are modest in scope, targeting a minimal number of cloud processes. Also, each of these well-developed examples shows some promise that further research will reveal a single mechanism generating most of the correlation between current and future climate parameters, leading to a true emergent constraint.

A comment about correlation strength. Because emergent constraints rely on statistical correlations across a model ensemble, one might be tempted to also consider statistical aspects such as the variance explained and insensitivity to outlier models in judging the reliability of an emergent constraint. However, in absence of physical explanation, we do not think it helpful to consider statistical aspects given the ever-present possibility that the emergent constraint arises through a fortuitous correlation. Indeed, Caldwell et al. (2014) have shown that after accounting for the lack of model independence, the distribution of correlation coefficients of a large ensemble of current climate predictors with CMIP5 equilibrium climate sensitivity is indistinguishable from that arising by chance alone. Thus, even large correlations can arise by chance in an ensemble. Of course, a higher correlation between current and future climate parameters will correspond to a larger spread reduction in the future climate projections when an emergent constraint is found, and models are eventually constrained with it. In this sense, a high correlation is desirable and even necessary if the emergent constraint is to have practical value, and all the examples we discuss here involve reasonably high correlations. However it cannot be considered a basis for the reliability of a particular candidate emergent constraint.

3. Recent examples

a. Low-level cloud optical depth

Building on earlier work (Tselioudis et al. 1992, Tselioudis et al. 1998), Gordon and Klein (2014) identified a possible emergent constraint for the optical depth of low-level clouds, a quantity proportional to a cloud's reflectivity. In this case, the current climate parameter is a model's sensitivity of optical depth to local surface temperature derived from variability at time-scales of daily to inter-annual in a number of different climate regimes. The future climate parameter is the relative amount of optical depth change in a model's climate change simulation (Figure 2a). Distinguishing by regime is necessary as it turns out that the change in optical depth for local temperature increases is generally positive when clouds are cold (for example, in polar and sub-polar regimes), while it only changes by small amount and is generally negative when the clouds are warm (for example, in the tropics). This differing behavior is present both in the climate change simulations and in the current climate.

In climate regimes such as the middle-latitude and polar regions, the correlation is quite high (r = 0.85/0.80, respectively) although the estimate from the current climate predicts too large a change in low-level cloud optical depth in some regions. (Note the general but not universal departure of each regime's collection of points from the one-to-one line.) The available satellite observations from Tselioudis et al. (1992) also show the same tendency of a positive temperature derivative at cold temperatures and a weak or negative one at warm temperatures. However, except perhaps at the coldest temperatures, the models have a positive bias relative to the observations, suggesting the models increase cloud optical depth too much with warming. Since the shortwave effects of low-level cloud optical depth changes outweigh their longwave effects at the top-of-the-atmosphere, this suggests simulated low-level cloud feedbacks should be more positive.

The increase in optical depth with temperature for cold clouds may stem from fundamental thermodynamics. The adiabatic cloud liquid water content increases appreciably with temperature at cold temperatures (Betts and Harshvardhan 1987). Consistent with this reasoning, the cloud water content of low-level clouds also exhibits 'emergent constraint' like behavior (Figure 2b). At cold temperatures, the multi-model mean temperature derivative of water content derived from current climate variability is close to that predicted by thermodynamics theory assuming adiabaticity (Gordon and Klein 2014). Other factors, such as the change from ice or mixed-phase cloud to more liquid dominant clouds (Tsushima et al. 2006), may contribute to inter-model spread and the models' positive bias with respect to observations.

At warm temperatures, the water-content-induced change under adiabatic conditions becomes very small. Correspondingly models do not generally exhibit optical depth increases with warming. The models' small optical depth decreases with warming and even larger decreases in observations must result from a different mechanism. Taking guidance from models that resolve cloud processes, *LES* of subtropical stratocumulus suggest the decreases in cloud optical depth with warming are due to cloud thinning. The thinning results from greater efficiency of convective mixing with dry air above the boundary layer upon warming (Rieck et al. 2012, Bretherton et al. 2013, Bretherton and Blossey 2014). Climate models may underestimate the observed decrease in optical depth with warming for warm low-level clouds because this mechanism is too weak or absent. At higher latitudes, the lack of this mechanism might also contribute to the model's positive bias to the increase in optical depth with warming. Indeed, to fully accept this as an emergent constraint, future work is needed to isolate the relative roles of adiabatic water content changes, phase partitioning, and convective mixing in contributing to inter-model variations in the temperature sensitivity of optical depth. This is needed to be sure that if a model were tuned to match the observed temperature of sensitivity of optical depth that it would be for the right physical reasons.

b. Subtropical marine low-level cloud cover

Changes in cloud cover are more important contributors to inter-model spread in cloud feedbacks than changes in cloud optical depth (Zelinka et al. 2012). Studies have consistently found the differing climate responses of subtropical and tropical marine boundary layer clouds to be most responsible for inter-model spread in global mean cloud feedbacks (Boucher et al. 2013). For these clouds, Qu et al. (2014) have identified a potential path to an emergent constraint through examination of inter-model spread in climate model simulations of low-level cloud cover (*LCC)* changes over subtropical subsidence regions where stratocumulus and cumulus predominate.

Qu et al. (2014) analyzed the *LCC* changes from 21st century climate model simulations with the following framework:

$$\Delta LCC = \left.\frac{\partial LCC}{\partial EIS}\right|_{SST} \times \Delta EIS + \left.\frac{\partial LCC}{\partial SST}\right|_{EIS} \times \Delta SST$$

In this equation, *Δ* refers to the climate change over the 21st century in climate model simulations, whereas the partial derivatives are sensitivities of *LCC* to two large-scale environmental parameters: the Estimated Inversion Strength (*EIS*, Wood and Bretherton 2006) of the temperature inversion capping the boundary layer, and Sea Surface Temperature (*SST)*. These sensitivities are derived from inter-annual variability in current climate simulations. This model is similar to that used by Gordon and Klein (2014) for optical depth changes discussed in Section 3a, except that it includes an additional environmental parameter, *EIS*. Nonetheless, it turns out that the *EIS* parameter is not that essential, as most inter-model variance in the 21st century *LCC* change can be explained by the *SST* term and the *SST* sensitivity (Figure 3). It is possible to derive a satellite-based observational estimate for the sensitivity of *LCC* to *SST*, using inter-annual variability over the last 30 years. If the models agreed with these observations, their 21st century *LCC* decreases would be in the larger end of the model range, favoring more absorption of solar radiation in the future, and larger climate sensitivities. Earlier work by Bony and DuFresne (2005) on the correlation between inter-annual variability of shortwave cloud radiative effect and *SST* (their Figure 4) also hinted that subtropical low-level cloud feedbacks should be towards the larger end of model results.

An underlying assumption of this framework is that since the time scales associated with low-level cloud formation and dissipation processes are on the order of hours, low-level clouds must be in statistical equilibrium with large-scale environmental factors whose inherent timescales are order of days or longer (Stevens and Brenguier 2009). There is ample observational evidence for an association between *LCC* and *EIS* (Wood and Bretherton 2006), including evidence that the direction of causation is primarily from *EIS* to *LCC* (Klein et al. 1995), rather than the reverse. Furthermore, the physical mechanism by which *EIS* influences *LCC* is clear, namely, stronger inversions inhibit the mixing of dry free-tropospheric air into the boundary layer, keeping boundary layer relative humidity and thus *LCC* higher. However, the physical mechanism by which *SST* influences *LCC* (at fixed *EIS*) needs better elucidation. One possibility is that the *LCC* sensitivity to *SST* can be viewed as a surrogate for the sensitivity of *LCC* to the vertical gradient in specific humidity from the surface to above the boundary layer, given that variations in this quantity ought to be highly correlated with changes in *SST*. Indeed, *LES* analyses suggest that the increased vertical gradient in specific humidity is essential to the positive low-cloud feedbacks with *SST* warming. Specifically, with the increased turbulent vertical flux of water within the boundary layer in a warmer climate, less cloud is needed to produce a given amount of mixing across the inversion (all under conditions of no large *EIS* increases) (Bretherton and Blossey 2014). If so, this could be the physical mechanism behind the tendency, seen in *LES* models and observations, of an *LCC* decrease with increasing *SST*, under conditions of fixed *EIS*.

Qu et al. (2014) also showed that a significant reason some models underestimate the *SST* component of the *LCC* response is that they rely on so-called Slingo (1980)-like cloud parameterizations. These parameterizations predict *LCC* variations purely in terms of changes in lower tropospheric stability (which is closely related to *EIS*), based on observational evidence that *EIS* accounts for a significant fraction of *LCC* variance in the current climate. However, slaving *LCC* to lower tropospheric stability probably inhibits a model from simulating dependencies on other variables that may be more important for climate change response (Qu et al. 2014, Bretherton et al. 2013). It may make the most sense to parameterize *LCC* in terms of local relative humidity or total water relative to saturation, and let the resultant sensitivity of the boundary layer physics to environmental parameters determine how *LCC* will vary.

c. Lower tropospheric mixing and climate sensitivity

Mixing between the boundary layer and the free troposphere plays a central role in low-level cloud variations. So it is natural to ask if there is a relationship between a climate model's skill in simulating that mixing and its low-level cloud changes associated with climate change. Sherwood et al. (2014) follow this line of reasoning. Their potential emergent constraint also suggests that climate sensitivity is in the upper end of the model-simulated range (Figure 4). To measure simulated lower tropospheric mixing, Sherwood et al. (2014) consider both mixing at cloud scales resulting from parameterized circulations, and mixing resulting from resolved shallow-depth, large-scale circulations (Figure 5). The cloud-scale mixing is measured with an indirect method focusing on the vertical gradient of temperature and moisture between 700 and 850 hPa in the west Pacific warm pool. They argue that greater cloud-scale mixing will result in this layer being less stable, with a smaller decrease in relative humidity with height. Large-scale mixing is measured through the resolved vertical mass-flux in circulations encompassing the boundary layer and the lower troposphere. Such shallow circulations have been observed in the Eastern tropical Pacific and tropical Atlantic (Zhang et al. 2008), and it is in these regions that Sherwood et al. (2014) measure their simulated strength.

Combining normalized measures of cloud-scale and large-scale lower-tropospheric mixing, a lower tropospheric mixing index (*LTMI*) is defined. This index is found to have a positive correlation with a model's climate sensitivity. Correlations of *LTMI* with the climate changes in low-level clouds are also found, though they are smaller in magnitude. Sherwood et al. (2014) claim this results from the difficulty in measuring simulated low-level cloud characteristics. Observational constraints on *LTMI* are derived using radiosonde data from selected stations in the West Pacific warm pool for the cloud-scale mixing component, and re-analyses produced by numerical weather prediction centers for the large-scale mixing component. Observations indicate an *LTMI* value in the larger half of model estimates, suggesting the low-level cloud component of climate sensitivity is in the upper half of model results.

The physical explanation offered for this emergent constraint is as follows. In the tropics, both shallow and deep circulations ventilate the boundary layer. The deep circulations are responsible for most global precipitation. The associated latent heat release balances atmospheric radiative cooling. Upon warming, the radiative cooling increase limits the precipitation increase and associated water vapor depletion from the boundary layer by deep circulations to only 2 – 4% per Kelvin (Held and Soden 2006). On the other hand, water vapor depletion by shallow cloud-scale circulations is not subject to an energetic constraint, since these circulations do not contribute appreciably to total precipitation. Instead, it increases with the product of the lower tropospheric mixing rate and boundary layer specific humidity. If one assumes the rate of lower tropospheric mixing remains fixed as the climate warms, then the depletion of water vapor by shallow circulations will increase with boundary layer specific humidity. This increase follows Clausius-Clapeyron, around 7% per Kelvin of boundary layer warming.

These arguments imply that as the climate warms, shallow circulations assume a larger role relative to that of the deep circulations both in depleting boundary layer water vapor and balancing the addition of water vapor by evaporation from the ocean surface (whose increase is limited to 2 – 4% per Kelvin). This leads to a relative humidity reduction in the boundary layer and a low-level cloud decrease. One can also take into account the fact that the strength of this reduction will be proportional to the amount of lower-tropospheric mixing. Models with greater lower tropospheric mixing will exhibit a greater decrease in relative humidity and low-level cloud as the climate warms.

Sherwood et al. (2014) provide some evidence for this mechanism by examining water vapor tendencies in the few models providing the necessary output. However, a full demonstration of this mechanism is not possible with existing multi-model archives. For example, multi-model diagnostics on the relative amounts of water vapor depletion by shallow and deep convection are not generally available. Also, it would be useful to perform a complete diagnosis of the boundary layer moisture budget in selected climate models and/or construct a toy model to illustrate how the amount of drying of the boundary layer with climate warming relates to the strength of low-level convective mixing. Separately, Zhang et al. (2013) provide indirect evidence for the small-scale mixing component of the Sherwood mechanism. They configured climate models as single-column models driven by expected large-scale environmental changes for low-level clouds and found that models with more active shallow convection parameterizations simulate more positive low-cloud feedbacks.

d. Other potential emergent constraints

The three potential emergent constraints discussed above may eventually become true emergent constraints. They each have candidate physical explanations associated with them that are credible, even if work remains to determine which mechanisms are dominant and why. Other potential emergent constraints for cloud feedbacks and climate sensitivity have also recently appeared in the literature (Table 1). We deem these constraints to be less well-developed, primarily because they lack the beginnings of a convincing physical explanation. However some fail even the subsidiary criteria proposed above. An exception though is that of Zhao (2014) who offers a well-developed physical argument based upon the precipitation efficiency of moist convection, but demonstrates the constraint only within a multi-physics ensemble of a single climate model. It is hard *a priori* to know how many emergent constraints there could be, given the serendipitously assembled nature of the climate model ensembles. For example, there may be redundancies among some current climate predictors (Caldwell et al. 2014) and in this regard, one might expect that the constraints of Qu et al. (2014) and Sherwood et al. (2014) to be redundant because both involve subtropical marine boundary layer clouds with somewhat related physical explanations. However, these constraints are not at first glance obviously redundant since there is a poor inter-model correlation between $\left.\frac{\partial LCC}{\partial SST}\right|_{EIS}$ and *LTMI* or its small-scale mixing component (Qu, personal communication).

An interesting aspect of the three well-developed emergent constraints presented above is that they all involve low-level clouds. Is there any fundamental reason to expect low-level clouds to exhibit greater potential for emergent constraint behavior? Perhaps the boundary layer's tendency to react quickly to its local (as opposed to non-local) environment parameters may make it easier for the long-term response of low-level clouds be predicted from its behavior on short-time scales. Alternatively, the preponderance of emergent constraints for low-level clouds may simply stem from greater attention to low-level clouds, given their major role in contributing to inter-model spread in cloud feedbacks. In principle, we do not see reason why there could not be emergent constraints for other cloud types. For example, the relationship between tropical high-cloud altitude and the vertical profile of clear-sky radiative cooling might form the basis for an emergent constraint (Hartmann and Larson 2002). However, an emergent constraint for high-cloud altitude may not exist if there is not appreciable inter-model spread in its future climate prediction – a necessary condition for the existence of an emergent constraint. In fact, the large spread in low-cloud feedbacks may be another reason it has been relatively easy to find possible emergent constraints for these clouds.

4. Implications of emergent constraints for climate models, observations, and prediction

Emergent constraints, if deemed reliable, have important implications for climate models, climate observations, and climate predictions.

Prioritization of climate model development. Emergent constraints point to aspects of a model's simulation of current climate that are important for climate prediction. This is particularly helpful in the area of clouds, for it is difficult to know which of their many attributes deserve most attention. With an emergent constraint, modelers can focus on improving the fidelity of the relevant process, knowing a reduction in inter-model spread will result when it is simulated under anthropogenic forcing. Of course, it may be challenging to use guidance from an emergent constraint if the current climate parameter is not specific to a piece of model physics but is the outcome of interactions among many pieces. Furthermore, all of this presumes that model developers will pay attention to emergent constraints. In this regard, it is worth noting that the diversity across models in snow-albedo feedback did not narrow in CMIP5 models after the emergent constraint for the feedback was found in CMIP3 models (Hall and Qu 2006).

Prioritization of climate observations. Emergent constraints point to potentially observable quantities that might help constrain model predictions. Some current climate parameters, such as small-scale and large-scale mixing in shallow-depth atmospheric circulations or the precipitation efficiency of moist convection, may not be easy or even possible to measure. Current climate parameters relying on the relationship between variables diagnosed from inter-annual variability require stable long-term datasets, another practical barrier. A related issue is the size of the observational uncertainty relative to inter-model spread. Only when observational uncertainty is less than inter-model spread will projections be constrained, setting a minimum threshold for observational length and quality. However, for the three relatively robust emergent constraints discussed in this article, a significant fraction of climate models lie outside the nominal uncertainty bounds of the observational estimates, implying inter-model spread in future climate projections can be meaningfully constrained (Figures 1, 3, and 4).

However, these uncertainty estimates deserve greater scrutiny from observational scientists, as it is not clear that all sources of uncertainty have been accounted for.

Narrowing climate predictions. If emergent constraints with a solid physical basis and precise observational estimates are found, how much trust should then be placed in the climate prediction? One might be reluctant to trust the new ensemble with its reduced spread, because some deficiency could be present in all models causing a systematic bias to their predictions. For example, cloud feedbacks from middle-level cloudiness or tropical anvils associated with mesoscale convective systems may be missed simply because climate models largely fail to simulate these clouds (Klein et al. 2013, Tsushima et al. 2013). Nonetheless, the constrained model predictions should be more trustworthy than before, because a source of model error has been identified and reduced. Emergent constraints will never make the models perfect. Instead they allow limited community resources to be focused on the model biases that are most consequential for climate change. So far, when the emergent constraint technique has been applied to cloud, the results have indicated a potential narrowing of uncertainty, and a shift in the most likely outcomes. Each of the three better-developed emergent constraints we discuss here suggests higher values of cloud feedbacks and climate sensitivity.

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Tables

Reference	Current Climate Predictor	Future Climate Predictand
Well-Developed Emergent Constraints		
Gordon et al. (2014)	The sensitivity of low-level cloud optical depth with temperature	Low-level cloud optical depth feedback in different latitude regimes
Qu et al. (2014)	The sensitivity of subtropical low-level cloud cover to sea surface temperature	The 21st century change in subtropical low-level cloud cover
Sherwood et al. (2014)	The strength of small-scale and large-scale lower tropospheric mixing	Equilibrium climate sensitivity
Less Well-Developed Emergent Constraints		
Volodin (2008)	Difference in cloud amount between tropics and southern middle-latitudes	Equilibrium climate sensitivity
Volodin (2008)	Subtropical relative humidity in the middle troposphere and the boundary layer	Equilibrium climate sensitivity
Trenberth and Fasullo (2010)	Net radiation error for the Southern Hemisphere	Equilibrium climate sensitivity
Fasullo and Trenberth (2012)	Middle-tropospheric relative humidity in subtropical subsidence zones	Equilibrium climate sensitivity
Klein et al. (2013)	Skill metric for the simulation of the climatological distributions of cloud height and reflectivity	Net and shortwave global mean cloud feedbacks
Zhao (2014)	Precipitation efficiency of moist convection	Global mean cloud feedbacks

Table 1. Recent possible emergent constraints for cloud feedbacks and climate sensitivity

Figures

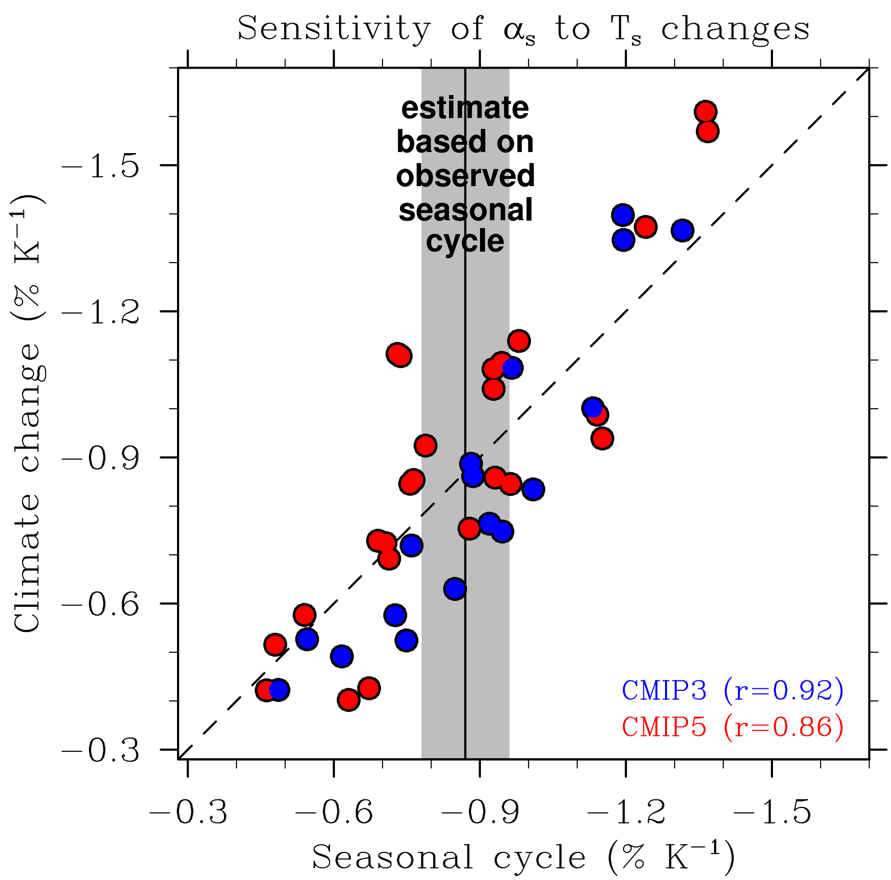

Figure 1. Scatterplot of the change in surface albedo $\Delta\alpha_s$ per degree of surface temperature ΔT_s warming for Northern Hemisphere land masses in the context of climate change versus that in the context of the seasonal cycle from CMIP3 (blue circles) and CMIP5 models (red circles). The dashed line is the best-fit regression line and the correlation coefficients for each model ensemble are indicated in the lower right corner. The thin vertical line is the observed estimate for the seasonal cycle and the gray shading surrounding this line is the statistical uncertainty of the observed estimate. (From Qu and Hall 2014)

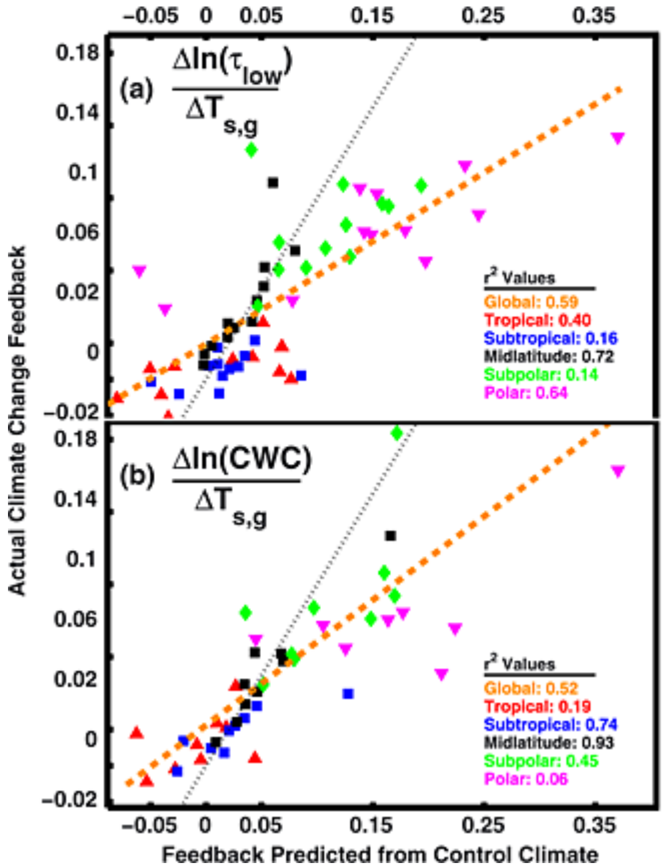

Figure 2. (a) Relationship in various climate regimes of CMIP3 and CMIP5 models between the low-level cloud optical depth (τ_{low}) feedback (in units of K^{-1}) predicted from the relationship of τ_{low} to surface temperature derived from current climate variability (on the abscissa) with the actual simulated climate change τ_{low} feedback (on the ordinate). More specifically, the "Feedback Predicted from Control Climate" is equal to the product of the derivative of the natural logarithm of τ_{low} with respect to surface air temperature in each region derived from current climate variability with the ratio of simulated regional to global-mean surface air temperature increase in CO_2-induced climate warming simulations. The "Actual Climate Change Feedback" is defined as the regional change in the natural logarithm of τ_{low} actually simulated under CO_2-induced climate warming normalized by the increase in global mean surface air temperature. Each symbol displays the value for a single CMIP3 or CMIP5 climate model with different shape-color combinations identifying the climate regime over which the relationship is calculated. The orange dashed line is the least squares regression line using the data from all regions together, and the black thin dashed line is a one-to-one line plotted for reference. The table inset displays the values of the linear correlation coefficient squared for regressions in individual climate regimes and for a regression using the data from all regions. The colors for the text in the table inset match those used by the symbols. (b) As in panel (a) but for the in-cloud value of condensed water content (CWC). (From Gordon and Klein 2014)

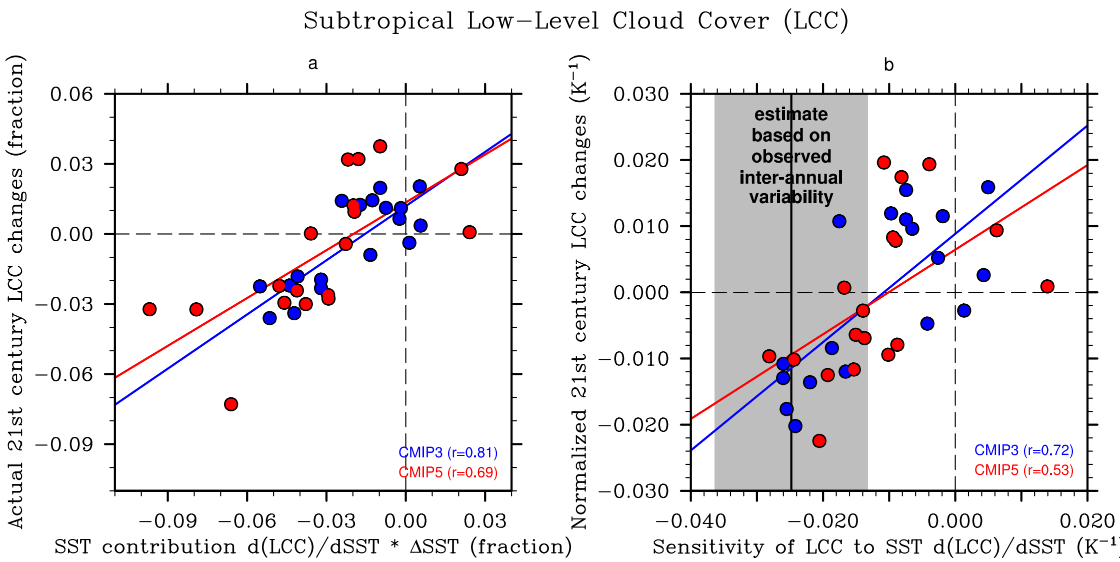

Figure 3. (a) Scatterplot of the Sea-Surface Temperature (*SST*) contribution averaged over the 5 primary subtropical marine stratocumulus regions versus actual 21st century fractional Low-Level Cloud Cover (*LCC*) changes averaged over the 5 regions. Solid line in each diagram represents a least-squares fit regression line with CMIP3 models color-coded in blue and CMIP5 models in red. Correlation coefficients for each model ensemble are indicated in the lower right corner. For each model, the *SST* contribution is defined as the product of that model's sensitivity of *LCC* to *SST* determined from inter-annual variability and the model's *SST* change over the 21st century. Note that the sensitivity of *LCC* to *SST* is calculated as a partial derivative holding the value of the Estimated Inversion Strength fixed. (b) As in panel (a) except that the abscissa is the *SST* sensitivity of *LCC* and the ordinate is the 21st century *LCC* change divided by the *SST* change over the 21st century. The thin vertical line is the observed estimate and the gray shading surrounding this line is the statistical uncertainty of the observed estimate. (From Qu et al. 2014)

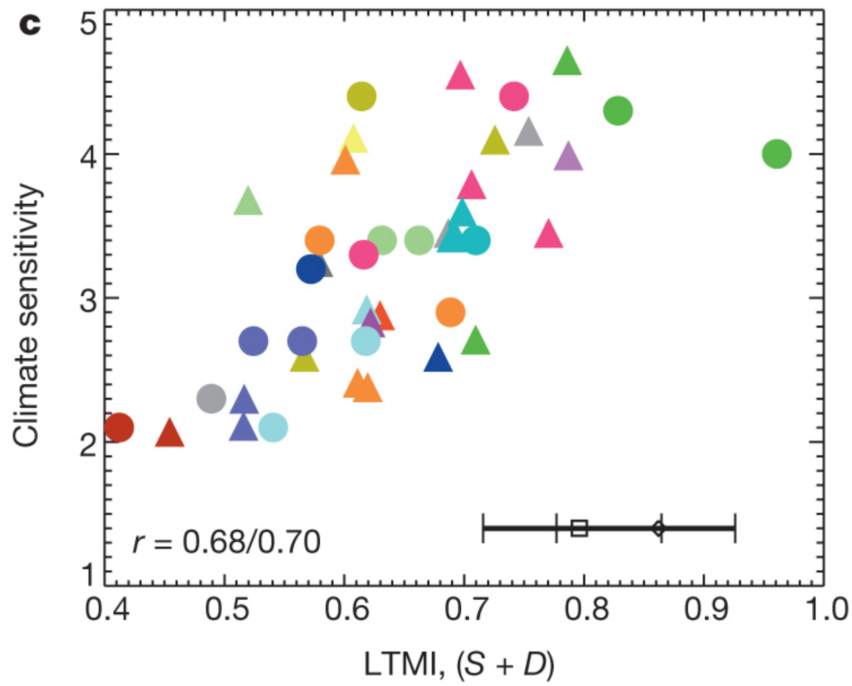

Figure 4. Scatterplot of the Lower-Tropospheric-Mixing-Index (LTMI) on the abscissa and the Equilibrium Climate Sensitivity (on the ordinate) from the 43 CMIP3 (circles) and CMIP5 models (diamonds). Linear correlation coefficients *r* are given in the lower left corner of LTMI with the Equilibrium Climate Sensitivity and the total system feedback, respectively. Two observational estimates with error bars for LTMI are shown near the abscissa axis with central values indicated by the unfilled square and diamonds. (From Sherwood et al. 2014)

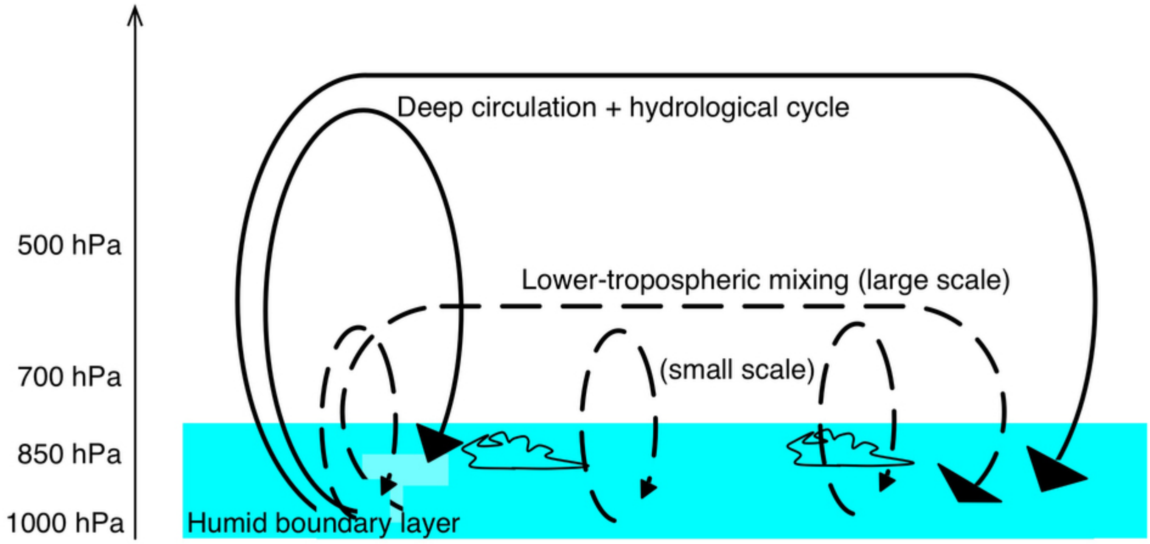

Figure 5. Schematic diagram illustrating tropical tropospheric circulations. Deep overturning circulations that strongly couple to the hydrological cycle and atmospheric energy budget are shown by solid lines. Lower-tropospheric mixing at both small and large-scales are shown by dashed lines. A mixing-induced low-level cloud feedback is proposed to result from the increasing relative role of lower-tropospheric mixing in exporting humidity from the boundary layer as the climate warms. The increased relative role of lower-tropospheric mixing under climate warming depletes the layer of the water vapour needed to sustain low-level cloud cover. (From Sherwood et al. 2014)